**BONE AGE:**

The bone age of a child indicates his/her level of biological and structural maturity better than the chronological age calculated from the date of birth. Radiography of the hand & wrist is the commonest modality used to calculate bone age.

When you turn 18 years old, the usual method of estimating the age of your bones by looking at X-rays of your hand and wrist doesn't work anymore. So, instead, doctors use a different part of your body called the medial end of the clavicle (collarbone) to estimate the age of your bones if you are between 18 and 22 years old. They require high CT and MRI scans which require intense research. [1]

**WHY TO STUDY BONE AGE:**

Bone age is often requested by pediatricians and endocrinologists for comparison with chronological age for diagnosing diseases which result in short or tall stature, impaired or accelerated growth, and delayed or early puberty.

The test also can help doctors monitor progress and guide treatment of kids with conditions that affect growth, including:

* diseases that affect the levels of growth hormones, such as growth hormone deficiency, hypothyroidism, precocious puberty, and adrenal gland disorders
* genetic growth disorders, such as [Turner syndrome](https://kidshealth.org/en/parents/turner.html)
* orthopedic or orthodontic problems in which the timing and type of treatment (surgery, bracing, etc.) are guided by the child's expected growth [4]

BA:Bone Age

BA is considered an important indicator of maturity and is the only size-independent indicator of biological maturity routinely used from birth to adulthood.

BA is delayed in children with constitutional delay of growth, growth hormone (GH) deficiency, hypothyroidism, malnutrition and chronic illness. BA is often marginally advanced in children with tall stature, premature adrenarche or overweight. Genetic overgrowth syndromes, such as Sotos syndrome, Beckwith-Wiedemann syndrome and Marshall-Smith syndrome, are associated with significantly advanced BA. [2]

Calculation of bone age is also employed for estimation of chronological age in conditions were accurate birth records are not available.

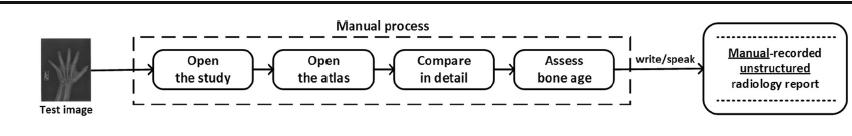
**DATASET**

RSNA Dataset: A data set consisting of 14 236 hand radiographs (12 611 training set, 1425 validation set, 200 test set). 12,611 training datasets, there are 5,778 female subjects and 6,833 male subjects, with an age range of 1–228 months, mainly specific to children aged 5–15 years, and each image is labeled with the true bone age. Images for the test set were obtained from Lucile Packard Children’s Hospital. [5]

**TEDIOUS WORK**

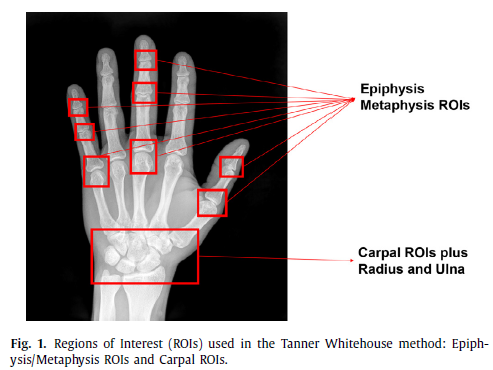
The bones on the X-ray image are compared with X-ray images in a standard atlas of bone development. The atlas is based on data from many other kids of the same gender and age. The bone age (also called the skeletal age) is measured in years. [4]

 A standard posterior-anterior (PA) view of the hand and wrist is ideal for visualization of features of hand bones.[7]



A brief description of the commonly used methods is given below.

1. ***The Greulich & Pyle (GP) Atlas****:*  It contains reference images of male and female standards of the left wrist and hand from birth till 18 years for females and 19 years for males. Also, explanation regarding the gradual age related changes observed in the bone structure is provided with each standard image. Bone age is calculated by comparing the left wrist radiographs of the subject with the nearest matching reference radiographs provided in the atlas which are standard for different ages provided in the atlas.[8]
2. ***Tanner Whitehouse (TW2) Method:***It is based on the age, rather it is based on the level of maturity for 20 selected regions of interest (ROI) in specific bones of the wrist and hand in each age population. The development level of each ROI is categorized into specific stages labeled as (A, B, C, D, . . ., I). A numerical score is given to each stage of development for each bone individually. By summing up all these scores from the ROIs, a total maturity score is calculated. TW method is comparatively more complex and requires more time; however it is more accurate and reproducible when compared to GP method. [9]
3. ***The Gilsanz & Ratibin (GR) Atlas****:*A new digital atlas developed by Vicente Gilsanz and Osman Ratibin[15](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3955574/#B15) in 2005. They produced idealized and artificial images specific for age and sex standards of skeletal maturity by thoroughly analyzing the size, shape, morphology and density of ossification centers in hand radiographs of healthy children, and generating images that include the typical characteristics of development for each of the ossification centers. The images of the new GR atlas are much more precise and have a better quality than those of the older GP atlas. . However the GR atlas had an increased number of outliers. Still it can be used to replace the older GP atlas.



**BONEXPERT**

A newer method for automatic bone age assessment called BoneXpert has been generated that rebuilds the edges of 15 bones of interest in hand radiographs .BoneXpert contains the following innovations:

1) a generative model (active appearance model) for the bone reconstruction;

2) the prediction of bone age from shape, intensity, and texture scores derived from principal component analysis;

3) the consensus bone age concept that defines bone age of each bone as the best estimate of the bone age of the other bones in the hand;

4) a common bone age model for males and females; and

5) the unified modelling of TW and GP bone age.

**RSNA TECHNIQUES:**

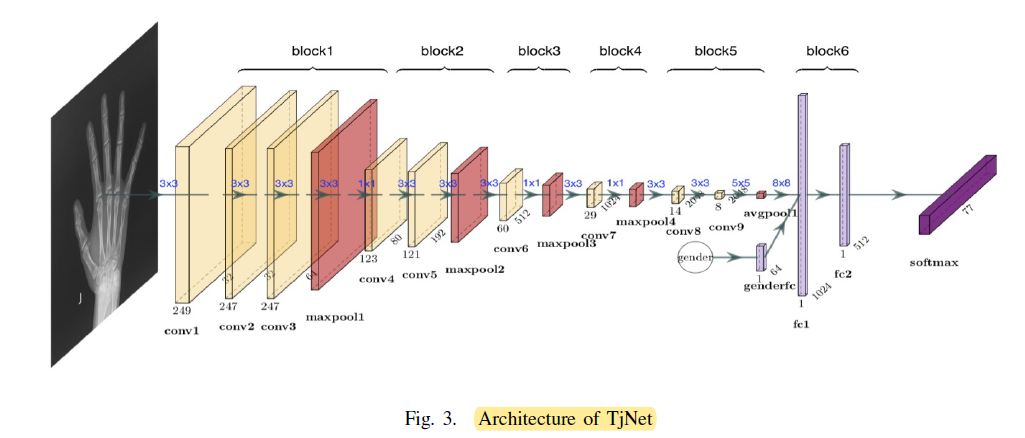
1. The Inception V3 architecture was used for the pixel information and was concatenated with the sex information. Data augmentation was done and finally , the combination of multiple high performing models in an ensemble approach was applied.
2. Each image was divided into 49 overlapping patches, The final prediction was calculated by taking 50th percentile of the patch prediction. This approach used transfer learning and fine-tuned ResNet-50 architectures pretrained on ImageNet Dataset.
3. This group developed a new variant of a convolutional neural network by creating the Ice Module. This model is considerably smaller than Inception V4. They split the data set into five parts and trained a model on each part. The best four parts were used for prediction on the test set, and their average score comprised the final output (simple ensemble).
4. Fourth group used conventional (nondeep) ML.The image preprocessing segmented the hand image into 15 bones. Bone age was estimated in each of the 13 bones by using hand-crafted features as opposed to features learned by deep learning.
5. The fifth-place approach was unique due to the creation of a segmentation mask module. A total of 400 manual segmentation masks for the hand, wrist, and distal forearm were created to train a dilated convolutional u-net to predict segmentation masks for the entire data set. It was then trained on masked images, which consisted of an ensemble of convolution neural networks with a final regression layer and a sex-embedding layer. [11]

**RESEARCH PAPERS**

1. **Improved Automatic Radiographic Bone Age Prediction with Deep Transfer Learning**

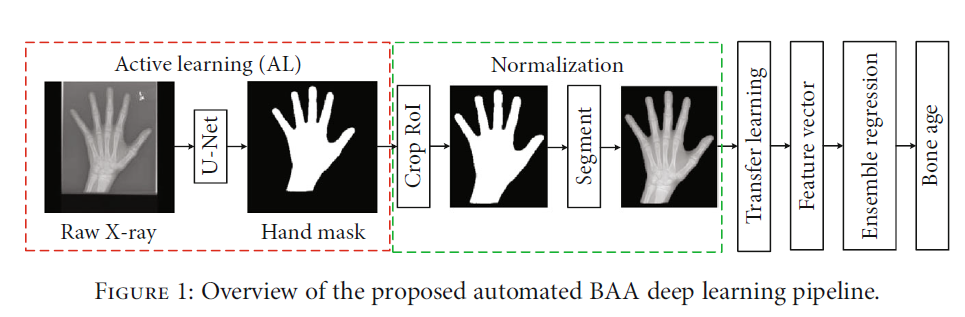
Dataset: RSNA dataset and Tongji Data

* proposed a CNN based network, TjNet, specifically designed to abstract the features contained in hand skeletal radiographs, to obtain the necessary representations for bone age classification. Pre-training TjNet, the transfer learning framework with TjNet achieves 0.169 years in MAD
* The best outcome when trained and tested with RSNA dataset, compared with Inception V4 and ResNet.



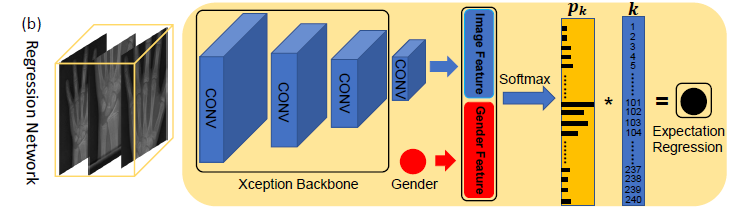
1. **Fully Automated Bone Age Assessment on Large-Scale** **Hand X-Ray Dataset**

* created a fully automated, deep learning-based pre processing pipeline to automatically detect and segment the hand and wrist, standardize the images, and perform BAA with pretrained deep CNNs and high efficiency regression model
* proposed a framework of medical image segmentation to relieve human expert annotation burden via deep active learning. Training with 200 manually annotated images .
* By using an ensemble technique,
* model achieved an MAE of 8.59, 6.96, and 7.35 months on all, male, and female cohorts of the dataset, respectively
* Dataset: RSNA

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1. **Attention-Guided Discriminative Region Localization and Label Distribution Learning for Bone Age Assessment**

* classification model to learn the attention maps for the hand region.
* second stage, we train a regression model to perform joint age distribution learning and expectation regression by aggregating different RoIs.
* they achieved the best result using the RSNA bone age dataset, 4.14 months MAD.



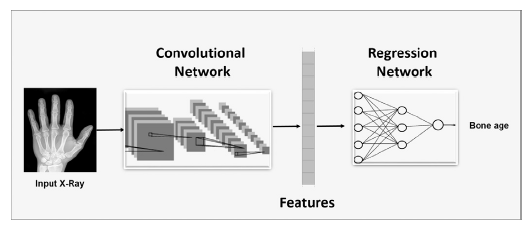
1. **Deep learning for automated skeletal bone age assessment in X-ray images**

* **Dataset:** Digital Hand Atlas Database System, a public X-ray dataset for auto- mated skeletal bone age benchmarking. The dataset contains 1391 X-ray left-hand scans of children of age up to 18 years old.
* It consists of

1. a convolutional network consisting of 5 con
2. volutional layers for feature extraction; and

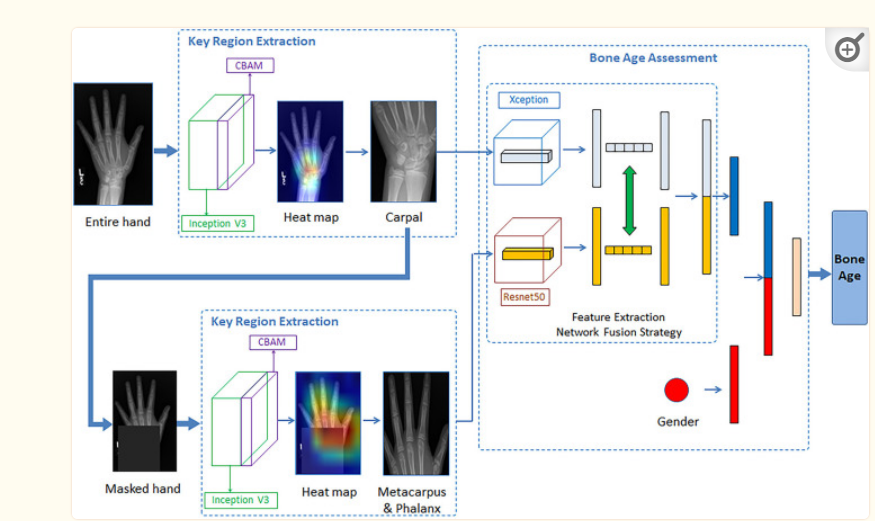
b) a regression network consisting of a set of fully connected layers (one or two) and a linear scalar output layer providing the bone age estimate.

* **BoNet**: it consists of five convolutional and pooling layers, aiming at the extracting low and middle-level visual features, and one deformation layer facing bone nonrigid deformation and two fully connected layers for bone age regression.



1. **Bone age assessment based on deep neural networks with annotation-free cascaded critical bone region extraction (**[**https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10017763/**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10017763/) **)**

* Proposed a two-stage deep learning method for BAA **without any manual region annotation**, which consists of a cascaded critical bone region extraction network and a gender-assisted bone age estimation network.
* First, the cascaded critical bone region extraction network automatically and sequentially locates two discriminative bone regions *via* the visual **heat maps.**
* Second, in order to obtain an accurate BAA, the extracted critical bone regions are fed into the gender-assisted bone age estimation network.
* The results showed mean absolute error (MAE) of 5.45 months on the public dataset RSNA)and 3.34 months on our private dataset.
* Dataset: RSNA , private dataset: CQJTJ dataset,  3,551 left-hand X-ray images 1,502 images are obtained from male subjects and 1,949 images are obtained from female subjects, with an age range of 13–218 months, mainly for children aged 4–16 years.



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[3]

[4] <https://kidshealth.org/en/parents/xray-bone-age.html>

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[11] Safwan S. Halabi, MD • Luciano M. Prevedello, MD The RSNA Pediatric Bone Age Machine Learning Challenge by the National Institute for Health Research U24CA180927 <https://doi.org/10.1148/radiol.2018180736>